Requirements Identification for Real-Time Anomaly Detection in Industrie 4.0 Machine Groups: A Structured Literature Review

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Abstract

Industrie 4.0 environments generate an unprecedented amount of production data. This is due to the rising number of sensors and interconnected devices capable of emitting data in millisecond frequencies. Streaming analytics offers promising methodologies that can support handling and analysis of data volume and variety. Transparency and control over real-time data can increase production efficiency in tightly connected machine environments. Data transparency may avoid time-consuming assessment of machines to detect anomalous machine behavior causing production inefficiencies or failures. This paper aims to identify requirements to implement streaming analytics for the detection of anomalies in Industrie 4.0 production machine groups through a structured literature review.

1. Introduction

The digitalization radically changes how manufacturing companies operate. Technological advancements, such as the embedding of sensor technology, allow for closer integration of machines and production data. The virtual representation of physical production activities through sensor data supposedly enables enhancement of production planning and control [1]. Recent digital advancements in manufacturing have spawned the fourth industrial revolution, denominated “Industrie 4.0” in Germany. In Industrie 4.0, interdependent machines cooperate and communicate with each other [2]. The integration of machines to groups supposedly increases manufacturing flexibility and shall cater to the needs of individualized production. On the downside of machine integration, unexpected behavior in one machine may lead to failure in a connected machine. The assessment of the entire group to find the failure’s root is time-consuming, especially when the assessment bases on stored, time-lagged data. Causal relationships in machine groups lead to a greater variety in potential failures in machine groups as compared to single machines [3]. Expert judgement as

recently applied method to detect unexpected behavior is time lagged and potentially subjective [4]. Also, small deviations from expected machine group behavior that do not result in failure, but lead to inefficiencies might remain unnoticed by experts. Analyzing production data in real-time seems to be a promising approach to overcome the outlined disadvantages. In contrast to batch data analysis and expert assessment, real-time analysis requires data to arrive in a continuous stream, which imposes specific challenges. The term “streaming analytics” subsumes methodologies to approach these challenges [5]. The immediate identification of unexpected behavior may constitute a basis for real-time decision making to mitigate failures. To understand what is needed for real-time anomaly detection, this paper addresses the following research question:

What are the requirements to implement real-time anomaly detection in machine groups in Industrie 4.0?

The paper structures into six chapters. Chapter two goes into detail on the structured literature review used as methodology to identify requirements. Chapter three briefly outlines characteristics of the found publications. Chapter four presents the identified requirements in detail. The requirements are supported by examples selected from literature. Chapter five includes an evaluation of the resulting requirements on the basis of interviews conducted with industry experts. Chapter six includes this study's limitations and starting points for future research. Lastly, chapter seven draws a conclusion.

2. Methodology

A systematic literature review following vom Brocke et al. was conducted to answer the research question [6]. At first, relevant scientific contributions were sought in the databases *Google Scholar*, *IEEE Xplore*, *Science Direct*, *Springer Link* and *Web of Science*. Table 1 shows the search string combinations used to find relevant literature. The left column

includes alternative search strings on anomaly detection and streaming analytics. These are combined with alternative search strings on Industrie 4.0 resp. equivalent terms shown in table 1's right column. The Industrie 4.0 equivalents were found subsequently in the identified literature. I.e., the German term Industrie 4.0 was the first term on table 1's right column, publications resulting from using this term for literature research included the terms Industry 4.0 and intelligent manufacturing. Further literature research on the latter terms resulted in the remaining equivalents. Google trend analysis shows that contributions to the Industrie 4.0 domain gained momentum after 2013 in terms of number of publications, so that the search was restricted to scientific publications after 2013. The search covers publications that included the search string combinations in title, abstract or text.

Table 1: Search string combinations

OR		OR
Anomaly detection		Industrie 4.0
Outlier detection		Industry 4.0
Real-time analytics	AND	Intelligent manufacturing
Sensor data analysis		Smart factory
Stream processing		Smart manufacturing
Streaming analytics		

The search initially resulted in 406 publications. Table 2 shows the steps taken to eliminate identified publications that do not fit this paper's research purpose. The findings presented in the following build on the remaining 44 cited publications. The identification of requirements as presented in chapter 4 bases on the recognition of concepts that were explicitly denominated as requirements or frequently reoccur in the cited publications. Specific requirements were identified in a structured approach that consists of three steps. In a first step, the literature was examined for common *requirement areas*. This examination resulted in the identification of three requirement areas. Secondly, a closer assessment of the requirement areas aimed to identify *requirement categories*. Lastly, the requirement categories identified in literature were subject to closer assessment to identify *specific requirements*.

3. Findings of literature

Most of the cited publications contribute with a case study, a framework or a combination of both. Other publications contain the development of algorithms or literature reviews, e.g.

The majority of authors do not go into detail on the industries their contribution applies to as shown in Table 3. The most frequently mentioned industries are aerospace and energy with four cited publications each.

Table 2: Elimination steps of structured literature review

Elimination measure	No. of eliminated publications	Reason for elimination
Screening (n = 406)		
Screen for duplicates	15	Duplicates
Screen for non-scientific publications	3	Exclusion of whitepapers
Coarse assessment (n = 388)		
Assess titles	211	Lacking relation to research purpose
Assess abstracts	108	Lacking or deviating focus that does not fit research purpose
Fine assessment (n = 69)		
Resulting publications	25	Publication background, focus or result do not fit research purpose
Resulting publications	44	

Table 3: Spread of contributions and industries

Contribution	Industry	Frequency
Case study	Not specified	4
	Energy	3
	Aerospace	2
	Food logistic	2
	Health	2
	Transportation	2
	Optic	1
	Automotive	1
	Not specified	9
Framework	Automotive	1
	Bio-medicine	1
	Energy	1
	Food	1
	Not specified	17
Other	Aerospace	2
	Robotics	1

Table 4 provides further details on the distribution of the kinds of contributions and industries. The cited publications divide into seven groups in terms of purpose. The most frequent purpose refers to algorithms developed to detect anomalies. The improvement of monitoring and control in production environments constitutes the second most frequently pursued goal. Only two publications refer to the development of data preparation techniques to increase data transparency and to enable more standardized data analysis.

Table 4: Purpose of cited publications

Purpose	Frequency
Development and testing of algorithms to detect anomalies in production.	15
Improvement of production process and machine monitoring and control on the basis of real-time data transparency.	12
Transformation of production environment towards real-time analytics to monitor machine behavior.	6
Calculation of anomalies' impacts and their mitigation.	3
Review of streaming analytics frameworks and implementations to reduce anomalies in production environments.	3
Increase of product quality and safety through the reduction of unexpected machine behavior.	3
Data preparation for real-time data transparency and analysis.	2

4. Requirements

To obtain a comprehensive structure, the requirements were divided into the areas of data, infrastructure and analysis, as shown in table 5. These requirement areas subsume ten requirement categories, among which four divide into two or three specific requirements.

4.1 Data requirements

The data requirements identified divide into requirements for data source and data composition.

Data source

Literature agrees on sensors as the most relevant source for data generation in Industrie 4.0. Sensors

Table 5: Requirements overview

	Requirement categories	Specific requirements	Frequency
Data	Data source	Sensors	27
		Domain knowledge	8
		Historical data	7
	Data composition		7
Infrastructure	Responsiveness	Scalability	13
		Latency	10
	Post-processing	Reconfigurability	12
		Evaluation	8
		Notification	5
	Communication		13
	Security		6
Analysis	Data preparation		10
	Data processing mode		5
	Analysis methodology	Supervised and unsupervised	10
		Supervised or unsupervised	5
	Analysis supervision		13

advanced from simple, mechanical devices to smart multi-sensory gadgets that allow real-time data access through digital interfaces. They enable Industrie 4.0 as they interconnect devices by communicating data that would else be unobtainable. Based on these data, production can be adjusted and machine groups can reconfigure. Without sensors, machine controllers would lack overview, which would hinder machine group control and thus autonomous production [7]. Kammerer et al. assess condition parameters of a packaging machine that loads pharmaceutical products into a box. The assessment bases on sensors that measure energy consumption and product location [8]. These parameters constitute the input for classification algorithms determining whether machine behavior deviates from expectation. As the sensors provide a multivariate continuous time-series, machine controllers can use the data for visual monitoring of different interdependent machine conditions.

Other cited publications point out that sensors do not only serve the elicitation of machine data, but also of production environment data [9], [10]. This becomes relevant in case environmental conditions influence production efficiency. Juric et al. prove sensors'

widespread application potential measuring various factors along a food cold chain, such as room temperature, humidity or light [9]. All sensors are part of a network that enables permanent surveillance of required conditions. Also, the data generated by the network constitutes a basis for process optimization along the food cold chain as inefficiencies become transparent.

Experts' domain knowledge as well as historical data constitute other data sources identified in the cited publications. Different from sensors, domain knowledge and historical data are not used for data generation, but for the enrichment of data analysis. Syafrudin et al. develop a framework, which uses real-time sensor data to predict manufacturing product quality [11]. To this end, data processing includes the offline storage of sensor data and previous analysis results in a database. This historical data is used as input parameters for product quality prediction algorithms. The inclusion of historical data increases prediction accuracy and thus product quality. Li et al.'s framework aims to structure the analysis of data rich, complex processes [12]. The authors propose event pattern matching for the identification of unexpected behavior along manufacturing. The design of event patterns requires judgement of experts, who can define process behavior that is expected in manufacturing. Thus, their anomaly detection approach depends on expert judgement data.

Data composition

Regarding the composition of data used for real-time analytics, literature shows the requirement to combine timestamps with measurement data. The succession of timestamps enables the creation of time-series that is necessary for continuous real-time monitoring.

4.2 Infrastructure requirements

Infrastructure requirements refer to the technical capabilities required in Industrie 4.0 to implement real-time analysis for anomaly detection. Four categories of infrastructural requirements were identified, namely requirements for technical responsiveness, post-processing and regarding the setup for data communication as well as infrastructural security.

Responsiveness

The usefulness of real-time data processing builds on high responsiveness resp. short waiting times [13]. Scalability is required to avoid lagging responses in case of infrastructural extensions or unexpectedly high

data volumes. 13 cited publications explicitly mention scalability as a requirement for anomaly detection. Analytical infrastructures have to be extensible, e.g. in case the frequency of sensor data emission rises. The proliferation of data generation and communication devices that comes with new machines or a tighter integration of sensors to production environments is only possible in scalable setups [14]. A frequently used measure to increase scalability for Industrie 4.0 analytics is the parallelization of data processing pipelines [11]. Some authors, such as Zalhana, Silaghi and Buchmann, Peres et al. or Han et al. achieve scalability of sensor generated streaming data by deploying custom software that allows demand-oriented addition of servers [15], [16], [17].

Several publications refer to the reduction of latency in different data processing steps, such as data generation, analysis and result evaluation [18]. Measures to keep latency low are increases in computation power as well as standardized communication interfaces. Zalhana, Silaghi and Buchmann put low-latency considerations at the core of their development of a data processing pipeline that serves the real-time generation of insights on sensor data [15]. The authors minimize latency by modularizing data processing and experimenting with the order of steps in their data pipeline [15].

Post-processing

Identified infrastructural requirements that are relevant after real-time data analysis divide into evaluation, notification and reconfigurability. Evaluation refers to the performance of algorithms or of entire real-time analysis architectures. The reasons for the requirement of post-processing algorithm evaluation are constantly changing input values and altering production systems [19]. Frequent algorithm assessment enables not only the choice of the most fitting one, but also the adjustment of algorithmic parameters.

Five cited publications describe the generation of notifications to alert the need for assessment. In case of unexpected production machine behavior, messenger systems connected to the analysis infrastructure trigger alarms or text messages. Employees, who are affected by the production anomaly receive the notifications and may take corrective action [20], [17].

12 cited publications point out the necessity of system reconfigurability. In case of detected anomalies, the production system needs to adapt in order to run as expected. Rakyta et al. explain that system reconfigurability comes with a trade-off [21]. On the one hand, the authors' implementation shows that reconfiguration can increase desired production

throughput and improve system functionality by reducing the likelihood of anomaly re-occurrence. On the other hand, reconfiguration requires costly flexibility that needs to be considered in design time. Also, each reconfiguration, regardless of its effectiveness, inherits changeover costs.

Communication

Data communication refers to transfers of sensor data, analysis results and notifications. Standardized communication interfaces and data transfer protocols are required to lower overall latency and to meet real-time constraints. 13 publications explicitly mention the use of protocols as requirement for their communication infrastructure. Most of the authors consider the Message Queuing Telemetry Transport protocol (MQTT) the de facto standard for the transfer of sensor generated stream data. Berry et al. make use of the protocol to ingest sensor data into a data processing cloud in a standardized and automated process [19]. In fact, the MQTT is used most frequently for sensor data transmission throughout the cited publications.

Security

Protocols and interfaces build the basis for data security. Six cited publications explicitly refer to the importance of data security in real-time anomaly detection. Carvajal Soto, Tavakolizadeh and Gyulai point out that the implementation of a sensor data analysis system would not be possible without sufficient security measures to maintain correct data accessible only by confidential employees [14]. Security measures identified in the cited publications include trusted devices, data encryption and network protection across all infrastructural components [22], [23], [24].

4.3 Analysis requirements

The analysis requirements reflect algorithmic and analytical capabilities necessary to leverage potentials for real-time anomaly detection in Industrie 4.0 environments.

Data preparation

Ten publications mention data preparation as prerequisite for subsequent value extraction. Preparation of sensor data includes the integration of data with different formats or types as well as cleansing erroneous or irrelevant data. Schutze et al. indicate that the variety of parameters measured by

sensors comes at the cost of data preparation [7]. Lacking data preparation hinders data compatibility and therefore joint analysis. Following Ding et al., missing values, inconsistencies and unexpected values are the main reasons for poor data quality that hinders value extraction [25]. The authors propose a framework with the aim to generate high quality data from sensor streams. However, the requirement to pre-process data leads to a trade-off in the real-time analysis context. Clean data foster better analysis results and more standardized analytical processes, but pre-processing as additional step between data generation and analysis must not take too much time to meet streaming analytics constraints.

Data processing mode

The majority of the cited publications refers to real-time analysis as online data processing. Data generated by sensors are captured, analyzed and then discarded. This has the advantage that the data does not have to be organized and managed in databases. On the downside, results are less comprehensible after analysis as the processed data is no more available.

Five publications explicitly mention a combination of online and offline analysis. Data analyzed in real-time is stored in a database after processing.

Marz and Warren outline a mass data analysis architecture that modularizes architecture components according to analysis needs [13]. The setup inherits modules for real-time and batch data processing. This so-called Lambda architecture enables real-time views as well as batch views on historicized, integrated data as response to user queries. Building on the Lambda architecture, Berry et al. implement a system that enables real-time processing of sensor data and the analysis of stored historical data [19]. They assess the performance of anomaly detection algorithms offline to evaluate in which cases which algorithms serve best to detect anomalous machine behavior.

Analysis methodology

The methodologies used to gain actionable insight on real-time data divide into supervised and unsupervised machine learning. Regarding supervised machine learning approaches, cited publications show the use of various data sources for algorithm training. Ali, Patel and Breslin present the case of a company that manufactures biomedical products, such as orthopedic knees [20]. The company makes use of regression-based production forecasting to adjust manufacturing processes and targets. To this end, historical data build the basis to train regression algorithms, which forecast production quantity at

various stages of the process. Identified examples of applied unsupervised machine learning include error forecasting in manufacturing processes through clustering [26]. Clustering algorithms are used to observe repetitive machine processes. The goal is to classify machine behavior that leads to expected outcomes and to differentiate deviant behavior that results in impaired products.

Five publications show the requirement to combine both unsupervised and supervised machine learning techniques.

Analysis supervision

13 cited publications present visual monitoring systems for real-time data analysis. The proliferation of sensors in Industrie 4.0 only leads to advanced monitoring and control capability in case the data is structured for a systematic overview [17]. Visual monitoring solutions divide into real image monitoring and graph monitoring in case data is not present in image form. Monitoring images of production processes requires domain experts capable of recognizing unexpected production results from images. French, Benakis and Marin-Reyes implement a prototype for robotic re-manufacturing of jet engine compressor blades used for aircraft vehicles [27]. Re-manufacturing includes error-prone welding processes, which require monitoring. To this end, a real-time image feed is implemented that enables experts to inspect the work pieces for errors. Different from that, Zenisek et al. develop a dashboard to monitor data generated by machine sensors in real-time [28]. Different views on various sensor data support experts in the visual identification of unexpected occurrences during production.

5. Evaluation

This section provides a brief qualitative evaluation of the results on the basis of interviews with industry experts.

5.1 Methodology

Four qualitative interviews with industry experts were conducted following the guidelines of Bryman, Bell and Harley [29]. The goal of the evaluation is twofold. On the one hand, the industry experts are supposed to validate the identified requirements. On the other hand, the interview might lead to further requirements that did not result from the structured literature review

Three interviewed industry experts have at least three years of experience working with machine groups

in Industrie 4.0 environments in the automotive sector. The fourth interviewee worked for a gear manufacturer that uses Industrie 4.0 machine groups to produce gears for industrial machines.

Each interview consisted of two phases to achieve a combination of unstructured and semi-structured interviews as proposed by Bryman, Bell and Harley [29]. The first part was an unstructured interview. After a short introduction to the topic, the interviewees were asked for requirements of anomaly detection in machine groups in Industrie 4.0. The unstructured interview allowed for an unrestricted, narrative answer. For the second phase, the interviewees were presented with table 5. After a short explanation, they were asked to comment on the results identified by the structured literature review.

All interviews were conducted separately and took about 45 minutes. The language spoken during the interview was German as all participants are native German speakers. We translated the results afterwards.

5.2 Results

The unstructured part of the interviews mostly confirmed the requirements identified through the structured literature review. Table 6 shows the expert interviews' results in relation to the literature review's results in terms of specific requirements resp. requirement categories in case there are no specific requirements. The experts' evaluation splits into the two interview phases in table 6. Two interviews revealed two additional requirements. The experts described the need for production process resp. machine behavior simulation before the first machine run and during production in defined time intervals. These simulations support the definition of expected machine group behavior. When the machines are running, the data generated during production is compared to the simulated data, which enables anomaly identification. Also, the interviews show a requirement for extensive machine testing to determine thresholds for values generated during production. These thresholds can vary among machine groups.

During the semi-structured part, the interviewees confirmed all identified data requirements. Two of them stressed the importance of domain knowledge as basis for anomaly detection. Regarding infrastructural requirements, the interviewees do not conform with internet protocols as method for sensor data communication. According to three of them, the data is mostly transferred through wires to a main computer. The other respondent confirms and adds that wireless sensor data communication is on experimental level. The industry experts could not assert to scalability as requirement due to lacking experience. All

interviewees emphasized the importance of latency in the real-time context. Two of them added that the entire production machine group stops in case a latency threshold is passed as this means that only lagged data is available. Also, all interviewees agree on the high importance of real-time machine data security. In their experience, the data is stored and processed in an internal infrastructure that does not enable access from outside the factory.

Table 6: Requirements summary

	Unstructured	Semi-structured
Sensors	✓	✓
Domain	✓	✓!
Historical data	✓	✓
Data composition	✓	✓
Scalability	–	–
Latency	✓	✓!
Reconfigurability	✓	✓
Evaluation	✓	✓
Notification	✓	✓
Communication	✓	✗
Security	✓	✓!
Data preparation	✓	✓
Data processing	–	–
Supervised and unsupervised	–	–
Supervised or unsupervised	–	–
Analysis supervision	✓	✓
Simulation	+	–
Thresholds	+	–

+ added, ✓ confirmed, ✗ denied, – none, ! stressed

Due to lacking experience, the interviewees could not validate the data requirements of offline and online data processing and analysis methodologies. They confirmed the need of data preparation, which takes place between data generation and visualization for user interfaces. The frequent use of these interfaces that are shown on screens attached to machines or tablets confirms the requirement of analysis supervision, in the interviewees' experience.

6. Limitations and future research

The applied methodology as well as the found results have some limitations as presented in the following. Despite the systematic literature review's rigorous approach, there is no guarantee that significant literature contributions were left unconsidered. This may be due to the choice of search strings or the elimination process. Also, the exclusion of contributions from before 2013 might reduce the

literature body by relevant publications. Most of the found literature was published as conference contributions, yet only a small share of the literature was published in journals. This may indicate a low level of maturity of the topic. Future researchers, who engage in the same or related fields may increase the topic's rigor and maturity by contributing to journals.

Moreover, some cited publications lack the explicit reference to requirements. Concepts that reoccurred in various publications were considered requirements although the authors do not denominate them as such. As literature on machine groups is also scarce, not all cited publications explicitly mention these, but e.g. refer to dependent production processes on different machines in the same plant [8].

The found requirements are independent from specific industries. However, some of the cited publications indicate that requirements significantly differ across industries. E.g., food cold chain logistics impose different analytical requirements than CNC machines in the aerospace industry [9], [26]. Requirements regarding the infrastructural setup may also differ with the size of the production plant and the number of the connected devices and data generating sensors.

This paper lays a foundation for further contributions, as to the best of our knowledge, there are no studies on industry neutral requirements for real-time data analysis of production machine group data in Industrie 4.0. The structured and modular presentation of the results in table 5 invites future researchers to extend the requirements by areas, categories or specific requirements. Further, the interviews' unstructured parts provide a basis for research on more requirements.

Follow-up research may take a broader scope that includes entire machine parks and broader real-time data landscapes. A broader scope may also include both batch and real-time processing in its research question, as this paper shows the requirement to combine both approaches. Moreover, future researchers and practitioners may use this paper's findings as a basis for a real implementation, which would verify the findings and may result in the discovery of new requirements.

7. Conclusion

Streaming analytics provide promising methodologies to master the vast data proliferation in Industrie 4.0 environments. Real-time data of production machine groups are specifically interesting as the machines work interdependently. Transparency over production data combined with streaming analytics methodologies build the basis for the

exploration and mitigation of anomalies during production.

A structured literature review was conducted to find requirements for the implementation of real-time anomaly detection mechanisms to improve machine group performance in Industrie 4.0. The search resulted in 44 publications. On this basis, this paper contributes with a structured presentation of these requirements ranging from high-level requirement areas to specific requirements. The synthesis of literature also enables an outlining of examples. The most frequent requirements identified in literature are the use of various sensors as data generators, scalability of data processing infrastructures and standardized communication interfaces that enable rapid data transmission and information generation. Qualitative interviews with industry experts resulted in a validation and extension of these requirements.

This paper contributes to both practice and research. From a researcher's perspective, the identified requirements constitute a starting point for theoretical advancements, such as an extension of table 5. Also, researchers might use this paper as basis for a prototypical implementation that meets the outlined requirements. Practitioners might use the contribution as guideline for the implementation of real-time analytics for anomaly detection in machine groups deployed in Industrie 4.0 environments.

10. References

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